Factors Associated with the Gender Gap in Bicycling Over Time

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ABSTRACT

Bicycling has grown in popularity over the past decade, but the gap in rates of bicycling between men and women in the United States (US) persists. This paper uses regional travel behavior study data from the Minneapolis-St. Paul Metropolitan Region in 2000 and 2010 to measure and model the gender gap in bicycling over time.

Findings from a series of statistical tests show that in aggregate, women bike less than men, and that growth in bicycling has been slower for women than for men over the past decade. However, stratifying the sample shows that women who live with at least one other adult bicyclist participate in bicycling at an equal rate as men. Similarly, frequency of bicycle trips among people who participate in bicycling differed by gender only slightly in 2000, and not at all in 2010. Binary logistic modeling results show that several factors, such as age and trip purpose, are associated with different bicycling outcomes for men and women, but some commonly hypothesized explanations, such as having children, were declining in effect or altogether insignificant.

These findings and conclusions are important for practice and research because understanding the nuances of the gender gap, such as the apparent gap in participation but not in frequency or the contagion effect of living with a cyclist, is essential for targeting programs effectively. This paper also identifies several travel behavior data collection limitations that complicate studying the gender gap, and offers recommendations for further study.

INTRODUCTION

Bicycling has grown in popularity over the past decade, but the gap in rates of bicycling between men and women in the United States (US) persists. After five years of investment in bicycling infrastructure and education under the Federal Nonmotorized Transportation Pilot Program (NTPP), the gender split for bicyclists in the Minneapolis-St. Paul metropolitan area remained constant at about 29% female *(1)*.

This paper uses a newly expanded dataset to explore the gender gap in bicycling over time. The Minneapolis-St. Paul metropolitan planning organization (Metropolitan Council) recently completed its decennial travel behavior inventory (TBI) study. The 2010 data, combined with data from the 2000 study, show that bicycling has increased in the region since the last TBI, but the gender gap has remained constant. These two snapshots in time, with a decade's worth of dedicated investment in bicycling, provides new opportunities to explore the nuances of the gender gap.

We propose six hypotheses about factors that may affect men's and women's decisions to bicycle differently, including trip distance, trip purpose, age, children in the household, weather, and geography. We use hypothesis tests to understand the nature of the gender gap, and binomial logistic modeling to test whether the hypothesized factors are significantly associated with bicycling, and whether that association differs for men and women.

This paper proceeds as follows. The next section reviews some of the literature about the gender gap in bicycling and gendered travel patterns more generally. The data and sampling procedures, variables, and analysis methods are outlined in the Methodology section. We present results from a series of hypothesis tests and four binomial logistic regressions, covering both participation in bicycling and tripwise mode choice. Finally, we offer conclusions and recommendations for future study based on the findings and the limitations and bias in common data collection practices that complicate studying the gender gap.

LITERATURE REVIEW

The gender gap in bicycling is well-known, and yet not very well understood. Many bicycle studies control for gender while modeling *(2, 3, 4)*, but only a limited number specifically target the gender gap in their hypothesis. Popular media coverage of the gender gap in bicycling focuses on a few main hypothesized causes: for example, risk aversion among women *(5)* and gendered economic and cultural forces that constrain women's travel *(6)*.

Emond et al. *(7)* tested a series of individual factors and social and physical environment conditions, and found that many of these affect men and women differently. Several of their variables had significant interactions with gender in a binary logistic model of participation in bicycling, including comfort level while bicycling, needing a car for travel during the day, biking in youth, self selection, and transit access *(7)*. Krizek et al. *(8)* focused on the impacts of bicycle facilities on men's and women's cycling. Women in their study were willing to travel farther out of their way to use dedicated facilities. They noted that trip purposes varied between men and women, in addition to safety perceptions and facility preferences and value. Twaddle et al. *(9)* found different patterns of participation and frequency for men and women. They discovered that men are more likely to be regular cyclists while women are more likely to be potential or occasional cyclists.

More generally, many studies have shown significant differences in men's and women's travel. Women on average make more trips but have shorter commutes *(10, 11, 12)* even after stratifying by occupational category *(10)*, though Gossen and Purvis *(12)* found that the commute distance gap closed between 1990 and 2000. They bear a disproportionate burden of care taking responsibilities (both children and elder care). McGuckin and Nakamoto *(10)* showed that women are more likely to chain trips and have less flexibility in their daily travel. Trip chaining in particular complicates how trip purposes are measured. Giuliano and Schweitzer *(11)* argue that policies designed to discourage auto use by increasing costs or uncertainty are "likely to disproportionately affect women" and that women place a higher value on travel time than men.

METHODOLOGY

Based on literature about the potential causal mechanisms for the gender gap, we identified six factors that may have different effects on men's and women's bicycling rates. This is not an exhaustive list of factors that may vary by gender, but an initial framework for exploring the gender gap.

1. Trip distance is differently associated with the likelihood that men and women will ride, with longer distances having a greater negative effect on women
2. Trip purpose is differently associated with the likelihood that men and women will cycle, with women being less likely to cycle for work due to complex travel patterns and different professional appearance standards for men and women
3. Weather may have a stronger impact on women specifically for commuting
4. Presence of children is likely to have greater effect on women to the extent that women on average still bear a disproportionate share of childrearing responsibilities
5. Older age may be more likely to reduce cycling among women
6. Geography, both as it correlates with distance and with jurisdictional policies that promote or hinder bicycling, will affect men and women differently

Data and Sampling

The Minneapolis-St. Paul metropolitan region comprises a 19-county metropolitan area, encompassing seven primarily suburban counties, 12 rural counties, and the two principal cities. The population of the seven county area in 2013 was 2.95 million; the population of the 19 county region exceeded 3 million. The Metropolitan Council administers a regional travel inventory study approximately every decade to inform transportation planning and modeling and other policy initiatives. Methodologies, basic descriptive statistics, and other results from the 2001 and 2010 TBIs are reported by the Met Council.

We obtained datasets from the TBIs conducted in 2001 and 2010; which were the first two inventories in the region to include questions about bicycling. The 2001 and 2010 TBIs differed in design and administration. The 2010 survey revised working of questions used in 2001, sampled more people but in one less county, and was administered over a longer time period (December 2010 through February 2011, versus April through August 2001, respectively). The sampling duration presents a particular problem for bicycling because it introduces a confounding effect of seasonality. We focus predominately on a sub-sample of the 2010 data, selected to match the months surveyed in 2000. Trip distances were estimated using GIS to plot origins and destinations and shortest path routing applications to calculate distance. All descriptive statistics and significance tests were computed using Stata 10.1.

We used binary logistic regression to analyze bicycling measured in two different ways. We estimated models for 2001 and 2010 data separately, but used the same variables in each to facilitate comparison. For each variable we test, we also test an interaction with that variable and gender. We also used exclusively binary variables in the models for ease of interpreting the interaction effects. Because the trip dataset contains multiple trips from the same people and households, including duplicate trips where multiple members of a household traveled together and each reported their own trip, we randomly sampled trips and people such that no household is represented more than once in either dataset. For the trip dataset, one bicycle or auto trip was sampled from each household. For the person table, one person who made bicycling and/or driving trips on their travel day was sampled from each household.

The structure of questions in the TBIs and our analytic choices have complex effects on measures of bicycling. For example, many trips were reported as starting and ending in the same location, making it impossible to estimate their distance traveled, so these trips were eliminated from the dataset. This action may reduce representation of purely recreational trips in our data. By focusing primarily on summer trips for compatibility with the 2001 survey, the bicycle mode share will appear inflated compared to a year-round average due to seasonality and weather effects. However, the extent of this problem is not clear. The 2001 survey spanned April through August, while biking tends to peak in September. Group quarters housing (e.g., college dormitories) were surveyed in September 2010, meaning that college students are under-sampled in the summer subset. The model focuses exclusively on adults, who may not be as inclined to bike as children or teens.

All subjects under 18 were removed from the dataset for this section of analysis. All subjects for whom the gender variable was missing were removed as well. We randomly sampled the dataset to include one adult per household.

Variables

Bicycling can be measured in a number of ways. For this study, we consider two binary measures: a trip-level variable (mode choice) and a person-level variable (participation). Participation is defined as an individual making one or more trips by bicycle at any time on their travel day, among people who made at least one trip by any mode.

Table 1 summarizes the independent variables used to measure these six hypotheses by showing the frequency of each binary variable for men and women in each survey year. Measures of trip characteristics (distance, purpose) are aggregated for the person model. A gender-interaction variable was created for all independent variables to see if the associations between these variables and bicycling differ for men and women.

HYPOTHESIS TEST RESULTS

Table 2 summarizes the two measures of bicycling for both survey years (participation and trip mode choice). Using χ^2 tests, we show that there is a gap in both percent of women participating in bicycling and in the percent of bicycle trips made by women. Rates of bicycling have increased by a significant amount between 2000 and 2010 (Table 2), but bicycling among men grew faster.

Table 3 summarizes the results from a series of χ^2 tests on the pooled 2000/2010 data,

TABLE 1 Independent Variables

	Trips					People			
	2000		2010			2000		2010	
Variable	Men	Women	Men	Women		Men	Women	Men	Women
Characteristics of this trip:					**At least one trip is:**				
Less than 5km	35.2%	42.2%	37.1%	40.5%	Less than 5km	23.1%	30.9%	24.5%	31.0%
Between 5 and 10km	20.8%	21.1%	21.5%	25.1%	Between 5 and 10km	26.0%	30.1%	27.8%	31.9%
Within Minneapolis	8.6%	8.3%	8.0%	7.5%	Within Minneapolis	14.2%	15.1%	14.8%	15.8%
Within St. Paul	3.5%	4.1%	4.9%	4.5%	Within St. Paul	6.0%	7.5%	8.4%	9.3%
Either starts or ends in Minneapolis	14.1%	11.5%	13.9%	12.5%		0.0%	0.0%	0.0%	0.0%
Either starts or ends in St. Paul	7.8%	7.4%	8.5%	8.5%		0.0%	0.0%	0.0%	0.0%
Home-based work	30.0%	24.0%	29.0%	19.2%	Home-based work	63.7%	52.3%	55.7%	41.6%
Traveling with another household member			74.8%	68.7%	Traveling with another household member			85.2%	84.0%
Characteristics of travel day:					**Characteristics of travel day:**				
Rain event	47.5%	44.1%	49.1%	50.0%	Rain event	46.6%	43.4%	48.6%	49.7%
Heat index exceeds high temperature	39.6%	42.3%	22.4%	23.7%	Heat index exceeds high temperature	38.7%	42.4%	24.0%	23.7%
Characteristics of household and individual:					**Characteristics of household and individual:**				
Children under 18	27.7%	28.3%	27.8%	23.7%	Children under 18	25.7%	28.3%	26.6%	22.7%
Age is 50 or older	35.2%	36.2%	56.2%	60.6%	Age is 50 or older	37.8%	39.6%	58.3%	63.0%
Lives in Minneapolis	15.5%	13.6%	14.9%	14.0%	Lives in Minneapolis	14.9%	14.7%	15.9%	15.0%
Lives in St. Paul	6.0%	7.1%	9.5%	8.8%	Lives in St. Paul	6.2%	7.1%	8.9%	9.6%
Female	0.0%	0.0%	100.0%	100.0%	Female	0.0%	0.0%	100.0%	100.0%
N	1,937	2,175	2,396	2,983	N	2,088	2,576	2,689	3,378

TABLE 2 Dependent Variable

	2000				2010			
	Male		Female		Male		Female	
Number and percent of trips made by:								
Bicycling	117	6.0%	63	2.9%	213	8.9%	120	4.0%
Auto	1,820	94.0%	2,112	97.1%	2,183	91.1%	2,863	96.0%
TOTAL	1,937	100%	2,175	100%	2,396	100%	2,983	100%
Gender difference?		$\chi^2 = 24.1904$	$p < 0.000$			$\chi^2 = 54.1972$	$p < 0.000$	
Difference between years for women?						$\chi^2 = 4.6625$	$p < 0.031$	
Difference between years for men?						$\chi^2 = 12.3611$	$p < 0.000$	
Number and percent of people who made:								
1+ Bike trip(s)	53	2.5%	37	1.4%	127	4.7%	74	2.2%
No bike trip(s)	2,035	97.5%	2,539	98.6%	2,562	95.3%	3,304	97.8%
TOTAL	2,088	100%	2,576	100%	2,689	100%	3,378	100%
Gender difference?		$\chi^2 = 7.4002$	$p < 0.007$			$\chi^2 = 29.9721$	$p < 0.000$	
Difference between years for women?						$\chi^2 = 4.5452$	$p < 0.033$	
Difference between years for men?						$\chi^2 = 15.4698$	$p < 0.000$	

2001 summer data alone, 2010 summer sub-sample alone, and 2010 full year sample, about multi-bicyclist households. Men are about twice as likely to participate in bicycling as women if no other adult in their household bikes. However, among people who live with another adult bicyclist, the rates of bicycling increase almost ten-fold, and the gender gap disappears. This finding was significant for all data samples tested.

Additionally, these results show changing effects over time. The percent difference in number of women being the only bicyclist in the household and number of men being only bicyclist grew from 2000 to 2010. We can see the percent difference between participation rates for men and women decreasing over time. The ratio of female bicyclists to male bicyclists in single-biker households dropped from 0.464 in 2000 to 0.360 in 2010, but it grew in multi-biker households from 0.891 to 0.994.

TABLE 3 Summary of Chi2 Test Results for Multi-Bicyclist Households

	No other bicyclists			Other bicyclists		
	Men	Women	Sig?	Men	Women	Sig?
Pooled Data	2.88%	1.20%	0.000	19.63%	18.59%	0.833
2000 Summer	1.94%	0.89%	0.000	15.62%	18.60%	0.736
2010 Summer	3.70%	1.46%	0.000	21.33%	18.58%	0.642
2010 Full Year	2.62%	1.02%	0.000	23.33%	18.75%	0.398

TABLE 4 Oneway ANOVA Results for Gender and Age among Bicyclists and Non-bicyclists

	Pooled			2000			2010		
	Mean	SD	Sig	Mean	SD	Sig	Mean	SD	Sig
[a]Male Nonbicyclists	49.70	16.14	b,c,d	45.92	15.43	b,d	52.84	16.04	b,c,d
[b]Male Bicyclists	43.46	13.88	a,c	37.23	11.60	a,c	46.10	13.96	a,c
[c]Female Nonbicyclists	51.34	16.47	a,b,d	46.61	15.89	b	54.90	16.00	a,b,d
[d]Female Bicyclists	41.99	13.21	a,c	38.86	12.07	a,c	43.46	13.54	a,c
	F = 33.05 P = 0.000			F = 9.80 P = 0.000			F = 31.46 P = 0.000		

oneway age fem_x_biker if summer = 1, bonf t
bysort survyear: oneway age fem_x_biker if summer == 1, bonf t

TABLE 5 T-test Results for Frequency of Bicycle Trips Among Identified Bicyclists, by Gender

	Male			Female			Difference	
	Mean	SD	N	Mean	SD	N	2-tailed	1-tailed
2000	2.90	2.09	59	2,45	1.20	38	0.1811	0.0906
2010	2.62	1.71	134	2.48	1.31	81	0.5071	0.2536

Gender, Bicyclists, and Age

Table 4 shows that while there are statistically significant differences between the four groups tested (male and female bicyclists and non-bicyclists), a bonferonni post-hoc test found that the difference is largely due to bicyclists being younger than non-bicyclists, with no clearly gendered pattern. This challenges our hypothesis that age will affect women more strongly than men.

Table 5 shows the results from a t-test on whether the number of bicycle trips per person differs by gender, specifically among people who were identified as having made at least one bike trip on their travel day. Among people who biked on their travel day, rates of bicycling between men and women do not differ much. In 2000, the difference was barely significant at the $p<0.1$ level. In 2010, there was no significant difference between men and women.

This suggests that much of the remaining gender gap can be attributed to a participation gap, not an intensity gap. Between 2000 and 2010, the significant difference in number of bike trips per day disappeared. If the participation gap remained constant, then the gains we see over the past decade in closing the gender gap can be attributed to women who bike being able to bike more often.

MODELS

Table 6 provides an abstract summary of all eight models tested. The first four model participation in bicycling on the person's travel day, and models 5 through 8 focus on tripwise mode choice. For each year within these sets, the model is shown two ways: one simple version with no gender interaction variables, and one full model with all explanatory variables interacted with gender. Detailed results for the full, interacted models are presented in Tables 7 and 8.

TABLE 6 Variable Summary of Simple and Full (with interactions) Trip Mode Choice and Individual Participation Models

	Person model						Trip Mode Choice Model					
	2000			2010			2000			2010		
Variable	Simple Coeff	Full Coeff	X	Simple Coeff	Full Coeff	X	Simple Coeff	Full Coeff	X	Simple Coeff	Full Coeff	X
Trip Characteristics												
Network distance < 5km	+	+	0	+	+	0	+	+	0	+	+	0
Network distance 5 - 10km	+	+	0	+	+	0	+	+	0	+	+	0
Within Minneapolis	+	+	0	+	+	0	0	0	0	+	0	0
Within St. Paul	+	+	0	+	+	0	0	0	0	+	+	0
Starts or ends in Minneapolis	0	0	0	+	+	-						
Starts or ends in St. Paul	+	0	0	+	+	0						
Home-based work	+	0	+	+	+	0	0	0	+	+	+	0
Travel Day Characteristics												
Rain event	-	0	0	-	-	0	0	0	0	-	0	0
Heat index > temperature	0	0	0	+	0	0	0	0	0	+	0	0
Household and Individual Characteristics												
Has kids	+	+	0	+	+	0	-	-	0	0	0	0
Age is 50 or older	-	-	0	-	-	-	-	-	+	-	-	-
Lives in Minneapolis							+	+	0	+	+	0
Lives in St. Paul							0	0	0	0	0	0
Female	-	-		-	0		-	0		-	0	
Constant	-	-		-	-		-	-		-	-	

+ indicates positive and significant at $p<0.1$
- indicates negative and significant at $p<0.1$
0 indicates $p\geq0.1$

TABLE 7 Trip Mode Choice Model Results

	2000			2010		
Variable	Coeff	P-Val	OR	Coeff	P-Val	OR
Trip Characteristics						
Network distance < 5km	2.41	0.000	11.17	2.14	0.000	8.47
Network distance 5 - 10km	1.31	0.003	3.71	1.26	0.000	3.54
Within Minneapolis	1.56	0.000	4.77	1.97	0.000	7.19
Within St. Paul	0.81	0.044	2.25	0.57	0.072	1.76
Starts or ends in Minneapolis	-0.22	0.664	0.80	1.47	0.000	4.36
Starts or ends in St. Paul	0.84	0.105	2.32	0.52	0.079	1.68
Home-based work	0.02	0.955	1.02	0.99	0.000	2.70
Gender - Trip Interaction						
Network distance less than 5km	0.29	0.707	1.33	-0.11	0.824	0.90
Network distance 5 to 10km	0.16	0.848	1.17	0.39	0.410	1.48
Within Minneapolis	0.32	0.420	1.37	-0.15	0.646	0.86
Within St. Paul	-0.59	0.433	0.56	0.43	0.361	1.54
Starts or ends in Minneapolis	0.64	0.437	1.90	-0.91	0.033	0.40
Starts or ends in St. Paul	-0.38	0.685	0.68	-0.14	0.786	0.87
Home-based work	0.83	0.046	2.29	0.05	0.882	1.05
Travel Day Characteristics						
Rain event	-0.28	0.184	0.75	-0.28	0.075	0.75
Heat index > temperature	-0.11	0.610	0.90	0.29	0.108	1.34
Gender - Travel Day Interaction						
Rain event	-0.16	0.659	0.85	-0.06	0.820	0.94
Heat index > temperature	-0.24	0.503	0.79	0.03	0.909	1.03
Household and Individual characteristics						
Has kids	0.58	0.011	1.78	0.83	0.000	2.28
Age is 50 or older	-1.26	0.000	0.28	-1.04	0.000	0.35
Female	-1.58	0.052	0.21	-0.45	0.388	0.64
Gender - Household and Individual Interaction						
Has kids	0.31	0.417	1.36	-0.41	0.168	0.66
Age is 50 or older	0.69	0.152	2.00	-0.62	0.059	0.54
Constant	-4.50	0.000	0.01	-4.45	0.000	0.01
N		4112			5379	
LL		-573.46			-946.23	
Pr Chi^2		0.000			0.000	
Pseudo R^2		0.2242			0.2424	

TABLE 8 Individual Participation Model Results

	2000			2010		
Variable	Coeff	P-Val	OR	Coeff	P-Val	OR
Aggregate Trip Characteristics						
Avg. network distance < 5km	1.75	0.000	5.78	1.25	0.000	3.49
Avg. network distance 5 - 10km	1.27	0.004	3.55	0.73	0.006	2.07
Within Minneapolis	0.00	0.993	1.00	0.54	0.101	1.71
Within St. Paul	-0.44	0.621	0.64	0.78	0.067	2.18
Home-based work	-0.18	0.551	0.83	0.71	0.001	2.03
Gender - Trip Interaction						
Avg. network distance < 5km	-0.39	0.577	0.68	0.39	0.439	1.48
Avg. network distance 5 - 10km	-0.50	0.485	0.61	0.37	0.474	1.45
Within Minneapolis	1.20	0.141	3.32	-0.15	0.791	0.86
Within St. Paul	0.56	0.660	1.75	-0.19	0.788	0.82
Home-based work	1.18	0.018	3.24	-0.31	0.345	0.73
Travel Day Characteristics						
Rain event	-0.13	0.667	0.88	-0.22	0.247	0.80
Heat index > temperature	-0.15	0.627	0.86	0.23	0.290	1.25
Gender - Travel Day Interaction						
Rain event	-0.54	0.264	0.58	-0.29	0.369	0.75
Heat index > temperature	-0.59	0.214	0.55	0.44	0.191	1.55
Household and Indiviudal Characteristics						
Has kids	-0.70	0.083	0.50	0.09	0.697	1.09
Age is 50 or older	-1.31	0.001	0.27	-0.46	0.027	0.63
Lives in Minneapolis	1.48	0.004	4.40	1.36	0.000	3.91
Lives in St. Paul	0.45	0.620	1.56	0.50	0.275	1.66
Female	-1.19	0.131	0.30	-0.59	0.313	0.55
Gender - Household and Individual Interaction						
Has kids	0.63	0.292	1.87	0.01	0.969	1.01
Age is 50 or older	1.02	0.065	2.78	-0.67	0.062	0.51
Lives in Minneapolis	-0.86	0.288	0.42	-0.03	0.960	0.97
Lives in St. Paul	-1.31	0.394	0.27	-0.52	0.522	0.59
Constant	-4.43	0.000	0.01	-4.58	0.000	0.01
N			4664			6067
LL			-371.16			-723.03
Pr Chi^2			0.000			0.000
Pseudo R^2			0.1649			0.1807

Model Fit

Binary logit regression does not have the R^2 measure in linear regression, where the value represents the percent of variation in the dependent variable that can be explained by the independent variables. Instead, the pseudo-R^2 measures the relative improvement of the model compared to a constant-only model, or a model with no variables. The interpretation is different, and while the theoretical range is from 0 to 1 like traditional R^2, the values tend to be a bit lower.

The pseudo-R^2 (McFadden's) values for the participation models range from 0.165 to 0.181 for 2000 and 2010. They are higher for the mode choice model, at 0.224 and 0.242 respectively. For both types of models, the pseudo-R^2 improves slightly between 2000 and 2010. The mode choice model performs better than the participation model, which is reasonable given the aggregated explanatory variables for the participation model.

Individual Participation Model

In 2000, network distance, children, age, and living in Minneapolis are significant both in the simple model and after gender interaction terms are added (6. Adding the interaction terms makes the binary gender variable insignificant, though most of the interaction terms themselves are also insignificant. Only female interacted with home-based work and female interacted with age over 50 are significant. The age coefficient is negative, meaning that being over 50 is associated with a reduced chance of making one or more bike trips on the travel day. The gender-age interaction term is positive, however, which mitigates some of this age effect for women. For men, being over 50 reduces the odds of biking instead of driving by a factor of 0.27.

The positive coefficient on home-based work trips contradicts our hypothesis that women are less likely to bike commute than men, relative to other trip purposes. Making shorter trips, living in Minneapolis, and not having children are associated with an increased chance of bicycling, but the effect for these does not vary between men and women.

In 2010, many of the same variables are still significant. Shorter trips, younger age, and living in Minneapolis are associated with increased odds of biking. Weather phenomena are significant before gender is controlled. The positive coefficient on hot and humid weather may be due to the relatively cold spring experienced in 2011 when the survey was being administered. Similarly to 2000, living in Minneapolis is positive and significant. Making trips within Minneapolis and St. Paul are also significant in 2010.

Adding gender interaction terms makes the binary gender variable insignificant, but the only significant interaction term is age. In 2010, the coefficient on the interaction term is negative, meaning that being over 50 is associated with a stronger reduction in odds of biking for women than for men. The relationship between bicycling, men, and age is waning; in 2010, they experienced a smaller dropoff in bicycling after the age of 50, while the bicycling gender gap appears to be expanding for older women. The 2000 results, and this reversal in 2010, are difficult to explain. The 2000 result in particular is contrary to our hypothesis about age affecting women more strongly in a negative direction, though one would expect an improvement between 2000 rather than a decline as the Baby Boomer generation reaches retirement age and has more leisure time. It is possible that increases in rates of bicycling over the past decade have been largely among younger people. Programming and new infrastructure have been concentrated in the urban core, which may correlate with age. Alternatively, it's possible that this is a reflection of shifting age cohorts such that the average age of women over 50 is increasing with longer life expectancies.

Trip Model

More variables are significant in all versions of the trip mode choice model, but like the participation model, most of the gender interaction terms are not significant. Home-based work trips interacted with gender is significant and positive in 2000, consistent with the participation model but contrary to our initial hypothesis. Evidence from the literature shows that women on average have shorter commutes and are more likely to chain several stops along their commute trip. The relationship between gender and bicycling for home-based work trips may reflect these attributes. In particular, the trip records are structured around single trips, not chains, so commute trips that include other stops, such as running errands or dropping children off at daycare or school, would not be classified as home-based work trips.

The gender-age interaction term in 2010 is significant and negative, also consistent with the participation model. The trip model reinforces the possibility that the gender gap is getting worse for women over 50.

Trips starting or ending in Minneapolis (but not both) has a negative interaction term. For men, a trip with one end in Minneapolis and the other outside the city increases the chances of bicycling being the chosen mode by a factor of 4.36 in 2010. The gender interaction term mitigates this effect for women, reducing her odds of bicycling for the same trip. Distance range for biking increased from 2000 to 2010 in both the participation model and the mode choice model, with no immediately apparent differences by gender. However, the significant interaction term on trips with one end in Minneapolis in 2010 is possibly related. Interjurisdictional trips will be longer on average than intracity trips, which may explain why the female interaction term is negative despite the effect for men being strong and positive.

Having children was positive and significant in both 2000 and 2010, with an increasing coefficient. Additionally, the interaction term with children was not significant for either year. This suggests that children may not be the source of a gender gap; indeed, having children appears to be associated with increased bicycling, possibly due to parents bicycling with their kids.

DISCUSSION

Progress or Stagnation?

The general take-away from the hypothesis tests and regression models is “mixed results”. Findings from the hypothesis tests show that women bike less than men, and that growth in bicycling has been slower for women than for men over the past decade. However, certain indicators demonstrate progress. Women in households with another bicyclist participate in biking at a rate roughly equal to men, and the share of women and men who bicycle is ten times higher in households with another bicyclist than households without. Among people who biked at least once on their travel day, an observed bicycle trip frequency gap in 2000 closed over the next decade, so that in 2010, there was no significant difference in trip frequency between female and male bicyclists.

In the mode choice models, commute trips were *not* associated with reduced likelihood of bicycling for women in particular. Additionally, the interaction term for women over 50, while negative and significant in the mode choice models for both years, decreased in magnitude over the decade. This directly contradicts the findings from the participation model, where the interaction between gender and age appeared to be worsening.

Recommendations and Implications

These findings and conclusions are important for practice and research because understanding the nuances of the gender gap is essential for targeting programs effectively. For example, the hypothesis tests show that the gender gap may be attributable to a gap in participation, but once that barrier is crossed, there was no observed gender gap in bicycling frequency. In this scenario, targeting programs at encouraging women to try bicycling may be more effective than encouraging female bicyclists to ride more.

The relationship between rates of bicycling and the presence of another bicyclist in the household, and the disappearance of the gender gap under these conditions, may demonstrate bicyclists self-selecting into relationships with other bicyclists, or it may be the product of a social contagion effect. More study is needed to identify what, if any, the causal mechanisms are between these two phenomena. If there is in fact a spillover effect and if the extent of that influence can be measured (e.g., is it strictly a household phenomenon, or does having bicyclist friends and neighbors also increase chances of biking), planners might be able to promote bicycling by facilitating interactions between bicyclists and potential bicyclists.

Data Needs and Bias

Several data limitations came to light during this study, and these limitations have implications for how the gender gap is measured. Trip chains are difficult to identify when travel diaries treat each component as a distinct trip. Research has shown that women are more likely than men to chain multiple stops into the commute trip. As a result, women's commute "trips" may be less easily identifiable as a commute trip. A chain during which the traveler drops their child off at school on the way to work would be classified as one home-based non-work trip and one work-based trip. The positive relationship observed in this sample between women, bicycling, and home-based work trips may actually be a relationship between women *who do not have obligations on the way to and from work*, bicycling, and commute trips.

Another data limitation that may produce biased results about the gender gap in bicycling is how trips with multiple people are classified. We used the variable "has children" as a proxy for whether a person has care taking responsibilities that would constrain their travel choices. However, a better measure would be simply how many other people accompanied the traveler on their trip. Both the 2000 and 2010 TBIs asked this question, and asked *which* household members were on the trip. However, the 2000 TBI only asked this question of people making trips by private auto. The assumption inherent in that survey protocol is that people who travel by any other mode are not picking up or dropping off passengers. By omitting this information for non-auto trips, it is impossible to test whether traveling with multiple people is in fact related to mode choice.

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